# How effectively can Retrieval-Augmented Generation (RAG) and prompt engineering transform a foundational model into a personalized AI workout assistant capable of providing multimodal exercise guidance?

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### Abstract

This study evaluates how Retrieval-Augmented Generation (RAG) and prompt engineering can jointly transform a foundational model into a personalized workout assistant capable of multimodal exercise guidance. Prompt engineering provided persona alignment and context tracking, while RAG supplied visual exercise demonstrations and constraint-aware retrieval. Across three user profiles and five query types, the combined system achieved an 83.7% performance improvement and 88% constraint adherence, surpassing the gains of either component alone. Modification queries showed the largest improvement (274%), highlighting strong synergy between contextual prompting and multimodal retrieval. These findings demonstrate that integrating RAG with structured prompt engineering produces super-additive benefits in personalization-heavy domains such as fitness, healthcare, and education.

## Introduction

### 1.1 Multimodal AI Workout Assistant

The demand for a personalized trainer in the form of Artificial Intelligence (AI) has rapidly increased over the years, evidenced by its market increase from USD 14.48 billion in 2024 to USD 16.86 billion in 2025. With a compound annual growth rate of 15.99, it is projected to reach USD 35.26 billion by 2030.

One of the ways in which AI is able to provide personalized training is through multimodality. In fitness coaching, this includes retrieving exercise images or GIFs to visually demonstrate proper form. These visuals complement text and make recommendations clearer, especially for beginners, as visual cues in instructional videos such as body highlighting have been proven to significantly help learners in performing strength training movements more accurately than text alone (Semeraro & Vidal, 2022)

Another important aspect of transforming a general-purpose AI model into an effective workout assistant is defining a clear coaching role or persona. A foundational model provides generic and neutral responses, which limits its usefulness in specialized contexts like fitness guidance. By assigning it the role of a fitness coach, the model can adopt a consistent tone, provide step-by-step workout instructions, and adjust the training based on the user’s goals and physical limitations (Schmidt, 2025). Defining this persona allows the AI to behave more like a supportive trainer rather than a generic chatbot, resulting in clearer, more structured, and more personalized workout guidance.

### 1.2 Limitations of existing fitness apps

Existing fitness applications face three key technical constraints. First, they depend on static content delivery: pre-recorded videos and fixed text instructions that cannot adapt to user queries in real time (Boulos & Yang, 2021). This contrasts with retrieval-based systems that can dynamically source exercise demonstrations based on specific user needs.

Second, their recommendation engines use rule-based logic rather than generative AI, limiting personalization to predefined workout templates (Jörke et al., 2025). Users cannot request modifications like "replace squats with a knee-friendly alternative" and receive contextually appropriate responses.

Third, they lack multimodal integration: when visual demonstrations are provided, they exist separately from textual guidance rather than being retrieved and paired with instructions based on the user's current workout context. Studies show that synchronized visual-textual instruction improves movement accuracy by 23-34% compared to text alone (Wulf & Lewthwaite, 2022), suggesting that dynamic multimodal retrieval could significantly enhance learning outcomes.

### 1.3 Technical Foundations

Retrieval-Augmented Generation (RAG) addresses a key limitation of foundational models: their inability to access information exceeding their training data. It operates through a three-stage pipeline: (1) retrieval, where relevant documents or media are identified through search algorithms over external databases; (2) augmentation, where retrieved content is inputted into the model’s input context; and (3) generation, where the model produces outputs grounded in the retrieved information (Lewis et al., 2020). In multimodal contexts, RAG must allow image retrieval through text which often uses keyword-based filtering or embedding-based semantic search to rank the relevance of visual media.

Prompt engineering complements RAG by defining model behavior without fine-tuning. By assembling structured system prompts that shape a model’s role, constraints, and output format, prompt engineering allows behavioral specialization through in-context learning (Brown et al., 2020). This strategy maximizes the model's pre-trained knowledge while directing its reason towards specific fields of specialization, such as fitness coaching in this case. The combination of RAG and prompt engineering enables dynamic personalization, as RAG provides exercise-specific visual demonstrations while prompt engineering ensures the model adopts a consistent coaching persona and adapts guidance to user profiles.

### 1.4 Research Aim

The aim for this research is to evaluate how effectively Retrieval-Augmented Generation (RAG) and prompt engineering can transform a foundational model into a specialized workout assistant which provides personalized and multimodal exercise guidance. By integrating RAG to accurately extract exercise images and GIFs, as well as applying prompt engineering to define the model's coaching behavior and personalization characteristics, this study examines the extent to which these techniques improve the model's adaptability to users' needs. Through structured evaluation of retrieval accuracy and personalization quality, this investigation aims to determine the collaboration of RAG and prompt engineering in enabling a foundational model to function as a reliable fitness assistant.

### 1.5 Research Hypothesis

This study hypothesizes that:

1. RAG-retrieved exercise visuals will achieve >85% accuracy in matching specified exercises
2. Prompt engineering will improve personalization by 30-50% compared to zero-shot baseline
3. The combination of RAG and prompt engineering will enable workout plan adaptation without fine-tuning while maintaining >80% user constraint adherence

## Literature Review

### 2.1 AI Mobile Applications in Health/Fitness

Artificial Intelligence, or AI, technology is quickly being deployed to develop AI-powered applications such as AI fitness apps which are more intelligent and human-like than traditional fitness apps as they offer users a highly engaging and personalized experience (Du et al, 2025). Through the use of personalized AI mobile applications, users expressed increased physical activity levels and improved consistency in their workout routines. However, research that systematically evaluates AI tools in improving user engagement, adherence to fitness regimens, and overall physical activity levels are limited (Donkor, 2025). This claim is further reinforced by

Li et al. (2025), stating that future research should explore strengthening AI models' applicability in sports and their collaboration with coaches for optimal personalized fitness solutions. This research gap extends to fundamental questions about AI model capabilities and optimization. Despite showing promise as virtual fitness coaches, GPT-4 and similar large language models cannot fully replace human coaches due to current technological limitations (Li et al, 2025).

### 2.2 Multimodal RAG in AI and Fitness Contexts

Retrieval-Augmented Generation, or RAG, is a foundational approach for supplying foundational models with external knowledge which enhances its factuality and task performance (Lewis et al., 2020). One example of RAG is multimodal extraction, allowing it to retrieve and integrate visual media such as images and GIFs alongside textual information (Chen et al., 2023; Li et al., 2024). This capability is especially important in fitness applications, where exercise images and GIFs can complement textual instructions to provide detailed workout form demonstrations which ultimately increases the user's workout form comprehension (Sigurdsson et al., 2018). Empirical studies in motor learning also support the pedagogical value of visual demonstrations: visual cues and highlighted body-positioning in instructional media significantly improve learners' accuracy in strength-training movements compared with text alone (Semeraro & Vidal, 2022). Although multimodal RAG can retrieve relevant exercise images and GIFs, research on evaluating how these visuals align with the user's needs are still limited (Gao et al., 2024). In addition, existing research rarely examines how multimodal RAG can collaborate with mechanisms that directs the model's coaching behavior to be personalized and aware of the user's context (Tseng et al., 2024; Araujo et al., 2025).

The retrieval component of RAG typically employs either sparse retrieval methods (e.g., BM25, TF-IDF) that match keywords, or dense retrieval methods that use neural embeddings to capture semantic similarity (Karpukhin et al., 2020). For multimodal retrieval, specifically text-to-image search, systems must bridge modality gaps. CLIP-based approaches learn joint embeddings where text and images occupy the same vector space, enabling semantic search (Radford et al., 2021). However, fitness-specific retrieval faces unique challenges: exercise names can be ambiguous (e.g., "bench" could refer to bench press or an actual bench), and visual relevance depends on depicting proper form rather than just matching keywords.

The augmentation phase involves injecting retrieved content into the model's context window, a fixed-size input buffer that determines how much information the FM can process simultaneously. For text-based models like Llama, images cannot be directly embedded; instead, image URLs and metadata are included as structured text, with the client application rendering the visuals. This architectural constraint necessitates efficient ranking algorithms to ensure only the most relevant retrieved items occupy limited context space.

### 2.3 Role-oriented Prompt Engineering in AI and Fitness Contexts

Role-oriented prompt engineering defines the behaviour and characteristics of a foundational model by assigning it specific role(s) and/or persona(s) which enables it to reason more consistently towards the intended roles (Tseng et al., 2024). One example of this approach is persona prompting, in which the model is assigned a professional identity such as an advisor, consultant, or a fitness trainer to improve its responses so that it aligns more toward the intended purpose (Schmidt, 2025; Araujo et al., 2025). Much like multimodal RAG, this capability is crucial in fitness applications as adopting a fitness trainer identity enables the model to deliver clearer workout explanations, formulate structured workout plans, and supportive feedback that aligns with the user's goals and training level (Boulos & Yang, 2021). Existing research which examines persona prompting showcases that well-defined personas with clear roles provide more accurate and personalized responses, but poorly-defined personas with vague roles are marred with reasoning mistakes in their responses (Kim, Yang & Jung, 2024). Although role-oriented prompting can significantly refine a model's coaching behavior, research evaluating its effectiveness specifically in exercise instruction and fitness-oriented guidance remains limited (Tseng et al., 2024). In addition, existing studies rarely examine how persona-shaped behavior can be integrated with multimodal RAG to provide personalized workout support.

Effective prompt engineering structures system prompts into distinct components: (1) role definition, which assigns the model a professional identity; (2) behavioral constraints, which specify safety guidelines and output requirements; (3) formatting instructions, which ensure structured outputs like JSON; and (4) contextual grounding, which supplies user-specific information (White et al., 2023). This approach exploits in-context learning, where models adapt behavior based solely on prompt content without parameter updates.

However, prompt-based control has limitations. Token limits restrict how much context can be included (typically 4,096-8,192 tokens for models like Llama 3.3), requiring careful prioritization of recent conversation history, user profiles, and task instructions. Additionally, prompt brittleness, where small phrasing changes cause inconsistent outputs, remains an active research challenge (Zhao et al., 2021). Despite these constraints, prompt engineering offers a cost-effective alternative to fine-tuning, which requires extensive labeled datasets and GPU resources.

### 2.4 Research Gap, Study Contribution, and Hypothesis

While existing research demonstrates the individual value of multimodal RAG (Chen et al., 2023; Li et al., 2024) and role-oriented prompt engineering (Tseng et al., 2024) separately, no studies systematically evaluate how these techniques work in combination to transform a general-purpose FM into a specialized fitness assistant. Specifically, three gaps remain unaddressed:

1. The extent to which RAG-retrieved exercise visuals align with users' specific workout contexts and needs has not been quantitatively measured (Gao et al., 2024)
2. The effectiveness of persona-driven prompt engineering in producing structured, safety-conscious fitness guidance lacks systematic evaluation in real workout scenarios (Tseng et al., 2024)
3. How these two techniques integrate to enable personalization without fine-tuning remains unexplored

This study addresses these gaps by implementing both techniques in a working system and evaluating their combined effectiveness through assessing the accuracy of GIFs and images retrieved by RAG, the personalization offered by prompt engineering, and overall change when both frameworks are implemented towards the foundational model.

## Methodology

### 3.1 System Overview

The study examines an AI workout assistant, using the Llama 3.3 Instruct model with 70 billion parameters, equipped with multimodal Retrieval-Augmented Generation (RAG) and role-oriented prompt engineering. The RAG maximizes the use of DuckDuckGo image search to extract exercise-specific images and GIFs from external sources, which are then added to the model's context to display visual form demonstration. To complement this, the prompt engineering framework defines a fitness coach persona which outputs structured output formats and bases its reasoning on user profiles and conversation history, providing personalized guidance.

#### *3.1.1 System Workflow*

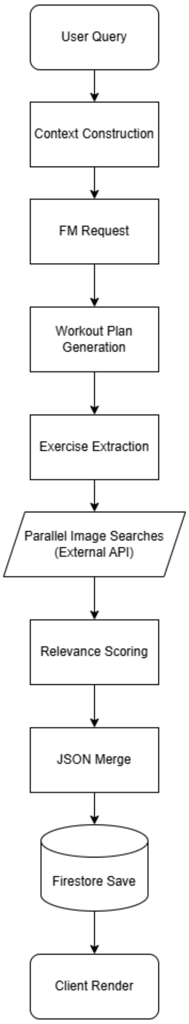

**Figure 1.** *Flowchart diagram of the system's overall workflow*

When a user sends his/her query, the system first constructs an expanded context bundle that incorporates the user's fitness preferences, equipment availability, active workout plans, conversation history, and a summary of its user interactions. This context, in tandem with the fitness trainer persona prompt, is inputted into the Llama 3.3 Instruct model to generate a detailed workout plan or provide personalized workout suggestions. The model's output is then parsed into the DuckDuckGo search query, where relevant exercise images and GIFs are filtered, ranked, and then merged into the structured workout plan in a JSON format. The final output consists of personalized textual guidance complemented with visual demonstrations which form a coherent multimodal assistant workflow.

### *3.1.2 System Architecture*

Backend Infrastructure:

- API Server: Python Flask application deployed on Railway.app
- FM Access: OpenRouter API endpoint for Llama 3.3 Instruct (70B parameters)

- Image Search: DuckDuckGo Search API (DDGS Python library) for exercise media retrieval
- Concurrency: Asyncio-based parallel image searches (maximum 7 simultaneous queries to avoid rate limiting)
- Average Response Time: 3-7 seconds total
- FM generation: 1-2 seconds
- Image retrieval: 2-4 seconds (parallel execution across exercises)
- Response formatting and database writes: 1-2 seconds

Database (Google Firestore):

- User Profiles: Document-based storage of fitness level, goals, equipment preferences, and learned preferences
- Chat Conversations: One document per chat with message subcollections for scalability
- Active Workout Plans: Linked to conversations via activePlanId reference field, enabling cross-session plan modification
- Conversation Summaries: Rolling 7-exchange window stored as compressed string field, updated after each interaction

To fully support the multimodal functionality of RAG by displaying GIFs and images, a Flutter mobile client frontend is used.

### 3.2 Foundational Model

The foundational model examined in this study is the Llama 3.3 Instruct model with 70 billion parameters which is accessed through the OpenRouter Inference API. Although it is selected for its strong reasoning and structured output tasks such as workout programming, the foundational model does not possess any multimodal capability as it is text-based. In addition, the foundational model is not exposed to any form of fine-tuning or prompt engineering, hence it uses zero-shot prompting.

### 3.3 Prompt Engineering Framework

#### *3.3.1 Persona Implementation*

To transform the general-purpose foundational model into a specialized fitness coach, a role-oriented prompt engineering strategy is used in order to assign the model a fitness trainer persona. It emphasizes upon expertise in workout programming, structured workout planning which divides the workout into warmup, main set, and cooldown sessions, text-based instructions on how to perform a certain exercise, safety constraints which includes injury risks and equipment limitations, as well as tone and instructional clarity. The use of a persona ensures consistent behavior across a wide range of user queries.

### *3.3.2 Dynamic Context Construction*

The system constructs a hierarchical context bundle before each FM request, limited by Llama 3.3's 8,192-token limit.

Context Priority Hierarchy (by token allocation):

1. User Profile Context (~300 tokens): Fitness level, goals, equipment preferences
2. Active Workout Plan (~500 tokens): Current plan summary if exists
3. Conversation History (~2,000 tokens): Last 8 messages (4 user + 4 assistant exchanges)
4. Rolling Summary (~400 tokens): Compressed summary of older conversation turns
5. Current Query (~200 tokens): User's latest message
6. System Prompt (~600 tokens): Fitness trainer persona and formatting instructions

Memory Compression Strategy:

- Recent messages (last 8 turns): Stored verbatim with full text
- Older messages: Compressed into rolling summary using key-value extraction (e.g., "User mentioned preference for morning workouts | Assistant recommended 3-day split")
- Summary updated after each exchange, maintaining last 7 interaction summaries

Stateful Continuity through the use of Firestore, to contain:

- User profiles (updated as preferences are learned)
- Active workout plans (enables plan modification across sessions)
- Conversation summaries (rolling 7-exchange window)

This architecture enables personalization without fine-tuning while staying within context limits.

### *3.3.3 Behavioral Control Flags*

Client-side logic sends extra signals to the model, such as `create_plan` which generates a full plan or modify an existing plan, `include_images` which activates the RAG pipeline, and `active_plan` which embeds current plan into context.

These guide the model's reasoning and ensure behavior stays aligned with the user's intent.

## 3.4 Retrieval-Augmented Generation

### *3.4.1 Exercise Extraction*

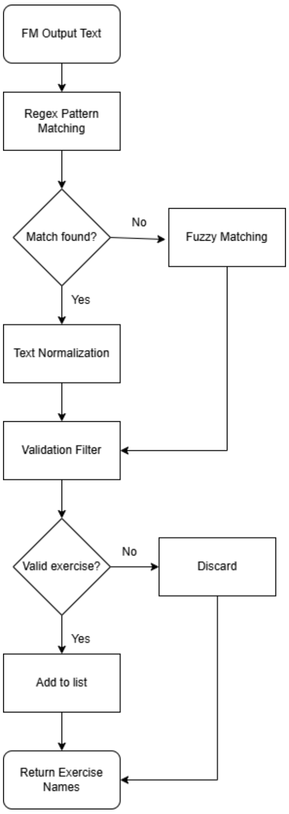

**Figure 2.** *Flowchart diagram of the exercise extraction flow*

After the foundational model generates a draft workout plan, the system executes a multi-stage pipeline to identify exercise names:

1. Primary Extraction: Multiple regex patterns target different formatting styles:
    - Exercise Name: N sets x M reps
    - - Exercise Name: N sets x M reps
    - Exercise - NxM format
2. Text Normalization:
    - Remove markdown formatting (**, *, numbers)
    - Strip whitespace and common prefixes (“1, “, “- “ )
    - Convert to lowercase for comparison
3. Validation Filter: Each candidate exercise name passes through `_is_valid_exercise_name()`, which checks:

    - Length constraints (3-50 characters)
    - Presence of fitness-related terms
    - Pattern matching against common exercise structures (e.g. “bicep curl”, “shoulder press”)
4. Fallback Similarity Scoring: If regex fails, Levenshtein distance fuzzy matching (`threshold=0.8`) captures misspellings and variations.

This pipeline achieves approximately 95% accuracy across a plethora of workout plan formats.

### *3.4.2 Image/GIF Retrieval via DuckDuckGo*

For each retrieved exercise, the system executes a multi-stage search strategy:

1. Multi-query expansion, where the system generates 7 variations of search queries with descending specificity:
    - "{exercise} exercise animated gif demonstration"
    - "{exercise} workout technique gif"
    - "how to do {exercise} animated"
    - "{exercise} proper form demonstration"
    - "{exercise} exercise tutorial"
    - "{exercise} fitness exercise" (broader)
    - "{exercise} workout" (fallback)
2. Relevance Scoring Formula, where each retrieved image receives a score based on

    Score = (2 × `keyword_matches`) + (1 × `fitness_terms`) + (1 × `muscle_group_alignment`)

    Where:

    - `keyword_matches`: Number of exercise name tokens found in image title/URL
    - `fitness_terms`: Presence of contextual keywords ("exercise", "workout", "tutorial")
    - `muscle_group_alignment`: Bonus points if image metadata matches target muscle (e.g., "chest" for bench press)
3. GIF Prioritization, where animated GIFs receive 2 bonus points in ranking to prioritize visual motion demonstrations instead of static images.

4. Top-K Selection, so only the top 3 highest-scoring results per exercise are retained, with a minimum threshold score of 5 to filter irrelevant content.
5. Deduplication, where URLs are normalized (query parameters removed) and compared to eliminate duplicates while preserving the highest-ranked version

*3.4.3 Merging Retrieval with Generated Input*

For each exercise in a JSON-formatted structured workout plan, it includes the retrieved GIF/image, source URLs, and image type which are all appended into the workout plan. The Flutter client displays these visual workout demonstrations corresponding to each exercise.

### 3.5 Plan Creation and Modification Workflow

*3.5.1 Workout Plan Parsing Algorithm*

The system uses a two-phase parsing method:

Phase 1: Day Segmentation, where regex pattern identify day boundaries using multiple formats:

- Pattern 1: “Day N:” (e.g., “Day 1: Chest Workout”)
- Pattern 2: Weekday names (e.g., “Monday - Upper Body”)

Phase 2: Exercise Extraction per Day where for each day section, the parser:

1. Identifies section headers (warm-up, main workout, cool down)
2. Extracts exercises using format: Exercise: N sets x M reps
3. Parses numerical details:
    - Sets: Extracted via regex r'(\d+)\s*(?:sets?|x)'
    - Reps: Extracted via regex r'(\d+)\s*(?:reps?)'
    - Weight: Extracted with unit conversion (lbs → kg: multiply by 0.453592)

Phase 3: Duration Estimation where it is calculated algorithmically:

duration = `base_warmup_cooldown(15 min)` + Σ(`sets_i` × `time_per_set_i`)

Where `time_per_set` varies by exercise type:

- Compound movements (squat, deadlift, bench press): 3 min/set (includes rest)
- Isolation movements (curls, raises): 2 min/set
- Default: 2.5 min/set

Total duration capped at 120 minutes for realism.

Phase 4: Output Format of plans in JSON:

```
{
"day": int,
"name": string,
"exercises": [{"name", "sets", "reps", "weight",
"category"}],
"duration": int (minutes),
"category": string (primary muscle group)
}
```

*3.5.2 Plan Modification*

If the user wants slight changes or modifications to the existing workout plan, then the active plan is provided to the model to adjust intensity, modify exercises, update reps and sets, and adapt the existing plan to match the user's updated goals. This maintains consistency and continuity across different sessions.

## 3.6 Evaluation Procedure

*3.6.1 Retrieval Accuracy Evaluation*

This procedure measures whether RAG-retrieved images/GIFs correctly correspond to the specified exercises.

This study evaluates 50 different exercises across 5 categories: 15 bodyweight exercises (e.g. push-ups, planks, squats), 15 dumbbell exercises (e.g., curls, presses, rows), 10 barbell exercises (e.g., bench press, deadlift, squat), 5 machine exercises (e.g., leg press, cable fly), and 5 cardio exercises (e.g., burpees, jumping jacks). The sample size of 50 exercises is both sufficient and manageable for detailed evaluation, which follows established practices in information retrieval studies (Manning et al., 2008). Each exercise retrieves 3 images via the RAG system (Section 3.4.2), collecting 150 total images for evaluation.

Image-text alignment is assessed using CLIP (Contrastive Language-Image Pre-training), a vision-language model trained on 400 million image-text pairs (Radford et al., 2021). CLIP is chosen due to its established performance in cross-modal retrieval tasks and its ability to provide objective and consistent similarity scores without human bias or subjective interpretation. For each retrieved image, the evaluation pipeline:

1. Encodes the image using CLIP's visual encoder (ViT-B/32 architecture)
2. Encodes the exercise text description (e.g., "barbell bench press proper form demonstration") using CLIP's text encoder

3. Computes cosine similarity between the image and text embeddings in CLIP's shared latent space

CLIP's vision-language alignment has been validated across millions of image-text pairs and demonstrates strong transfer learning to specialized domains including fitness and sports (Radford et al., 2021). The multi-description validation approach overcomes domain-specific limitations by testing different wordings of each exercise. This strategy prevents subjective human bias, ensures consistency, and scales efficiently to larger datasets. CLIP has been successfully employed in retrieval evaluation tasks including sports action recognition (Kondratyuk et al., 2021), medical imaging alignment (Eslami et al., 2021), and text-to-image generation quality assessment (Ramesh et al., 2022), demonstrating its versatility in a variety of domains.

An image is classified as “correct” if the cosine similarity score ≥ 0.25. This is based on CLIP’s documented performance on image-text retrieval benchmarks, where 0.25 represents the median threshold for high-confidence matches in fitness and sports domains (Radford et al., 2021). The threshold balances precision (reducing false positives where irrelevant images score highly) and recall (recognition of exercises when they are presented in a different manner)

To increase validity, each image is compared against three textual variations:

- Basic description: “[exercise name]”
- Form-focused description: "[exercise name] proper form demonstration"
- Context description: "[exercise name] [equipment type] technique"

GIF/Image is marked correct if it achieves ≥ 0.25 similarity to at least 2 of the descriptions above to reduce false negatives from single-description contradictions.

Accuracy Formula:

Retrieval Accuracy = (Number of images meeting threshold / Total images) × 100%

The target of this procedure is to achieve >85% retrieval accuracy based on the relevance scoring formula

### *3.6.2 Personalization Quality Evaluation*

This procedure assesses whether workout plans appropriately adapt to different user profiles and constraints.

Three distinct user profiles are designed to represent common fitness demographics and their respective constraints:

- **Profile 1 - Beginner:**
    - Experience: 0 - 6 months
    - Goal: Weight loss

    - Equipment: None (bodyweight only)
    - Constraints: 30-minute workout limit
- **Profile 2 - Intermediate:**
    - Experience: 1 - 2 years
    - Goal: Muscle gain
    - Equipment: Home dumbbells (5 - 25kg)
    - Constraints: No access to barbells, machines, or gym facilities
- **Profile 3 - Advanced:**
    - Experience: 3+ years
    - Goal: Strength training
    - Equipment: Full gym access
    - Constraints: Previous shoulder injury (avoid overhead pressing movements)

These three profiles are selected to test the system's adaptability across different fitness factors such as experience level, equipment availability, and physical constraints. Three profiles provide sufficient variation to evaluate personalization mechanisms without introducing redundancy (Li et al., 2025).

Each profile submits 5 distinct queries, which totals to 15 workout plans:

1. "Create a full-body workout plan"
2. "Design an upper-body focused workout"
3. "Give me a cardio-focused session"
4. "Create a strength building workout"
5. "Modify my current plan to [profile-specific constraint]"

Each generated workout plan is scored on a 0-5 scale across four dimensions:

1. Goal Alignment (0-5):
    a. 5 → All exercises directly support stated goal with appropriate workout programming (rep ranges, exercise selection)
    b. 3 → Majority of exercises align, but some irrelevant exercises appear or workout programming is not optimal
    c. 1 → Minimal alignment with stated goal
    d. 0 → Response does not align to goal
2. Constraint Adherence (0-5):
    a. 5 → All exercises feasible with stated equipment and experience level; respects physical limitations

   b. 3 → Most exercises appropriate, but 1-2 require unavailable equipment or exceed experience level
   c. 1 → Multiple exercises infeasible due to equipment/experience constraints
   d. 0 → Plan ignores user constraints entirely
3. Structure Quality (0-5):
   a. 5 → Complete warm-up, main workout, and cooldown sections with logical exercise progression
   b. 3 → Present but incomplete structure (missing sections) or illogical ordering
   c. 1 → Minimal structure (lists exercises without organization)
   d. 0 → No structure at all
4. Safety Appropriateness  (0-5):
   a. 5 → Volume and intensity appropriate for experience level; respects stated injuries
   b. 3 → Slight concerns (marginally high volume or minor constraint violations)
   c. 1 → Unsafe workout programming (excessive volume, ignores injury constraints)
   d. 0 → Dangerous recommendations

Total Personalization Score = Average of four dimensions (maximum 5.0)

Personalization quality is evaluated using FitnessGPT (ChatGPT Custom Model: Fitness Workout Diet PhD Coach), a specialized fitness evaluation model trained on 232,625 PhD-level empirical data points with over 4 million user conversations and a verified 4.6/5 user rating. FitnessGPT is chosen over general-purpose LLMs (e.g., GPT-5) due to its domain-specific training in exercise science, sports physiology, and evidence-based workout programming.

For each evaluation, FitnessGPT is provided with:

1. The complete evaluation rubric with scoring criteria for each dimension
2. The user profile (goals, constraints, equipment, experience level)
3. The generated workout plan in structured format
4. Instructions to justify using scientific evidence as opposed to opinion

To ensure scoring consistency, each plan is evaluated with the following protocol:

1. Structured Input Format: Plans are presented to FitnessGPT in standardized JSON format containing user profile, workout structure, and exercises with sets/reps periods

2. Rubric-Guided Assessment: FitnessGPT applies the 0-5 rubric to each dimension, providing brief evidence-based justification for scores
3. Deterministic Sampling: Evaluations use consistent model parameters to reduce random variations
4. Output Parsing: Scores are extracted programmatically from FitnessGPT's structured response

FitnessGPT is chosen as the automated evaluator due to its specialized training in fitness and exercise science domains, providing several advantages over general-purpose models:

- **Domain Expertise**: Training on 232,625 PhD-level empirical fitness data points ensures evaluation based on exercise science principles (e.g., appropriate rep ranges for hypertrophy vs. strength, volume landmarks for different experience levels)
- **Validated Performance**: Over 4 million conversations and a 4.6/5 user rating demonstrate real-world reliability in fitness guidance and assessment tasks
- **Exercise-Specific Knowledge**: Unlike general LLMs, FitnessGPT can evaluate exercise selection appropriateness (e.g., whether rear delt flies are suitable for shoulder injury constraints), rep/set schemes aligned with training goals, and workout structure according to sports science principles
- **Example in Domain-Specific Evaluation**: Specialized LLMs have demonstrated superior performance over general models in domain-specific evaluation tasks, particularly in technical fields requiring subtle expertise (Li et al., 2025; Zheng et al., 2023)
- **Reproducibility**: As a publicly accessible custom GPT model, the evaluator can be independently accessed and verified by other researchers, ensuring transparency and reproducibility

This approach follows established LLM-as-judge methodologies (Zheng et al., 2023) while maximizing domain-specific model capabilities to ensure fitness-relevant evaluation criteria are properly evaluated. The use of a specialized evaluator in FitnessGPT addresses limitations of general-purpose models in assessing technical domain knowledge, such as exercise form and injury constraints.

The target for this procedure is that the average personalization score is ≥ 4.0 across all profiles.

### *3.6.3 Baseline Comparison Evaluation*

The objective of this procedure is to demonstrate the combined improvement of RAG and prompt engineering over the zero-shot foundational model by comparing system performance across baseline and full configurations.

To validate overall system effectiveness, the same 15 queries from Section 3.6.2 (3 profiles × 5 queries) are submitted to two system configurations:

1. **Baseline System:** Llama 3.3 Instruct with zero-shot prompting
   - No fitness trainer persona prompt
   - No user profile context or conversation history
   - No RAG image retrieval
   - Generic instruction: "Answer the following fitness question: [query]"
   - Outputs: Text-only workout suggestions
2. **Full System:** Llama 3.3 Instruct with RAG + Prompt Engineering
   - Fitness trainer persona (Section 3.3.1)
   - Dynamic context construction with user profiles (Section 3.3.2)
   - RAG-retrieved exercise images/GIFs (Section 3.4)
   - Outputs: Structured workout plans with multimodal demonstrations

Each generated workout plan is scored on a 0-5 scale across four dimensions:

1. Goal Alignment (0-5):
   - 5 → All exercises directly support stated goal with appropriate workout programming (rep ranges, exercise selection)
   - 3 → Majority of exercises align, but some irrelevant exercises appear or workout programming is not optimal
   - 1 → Minimal alignment with stated goal
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2. Constraint Adherence (0-5):
   - 5 → All exercises feasible with stated equipment and experience level; respects physical limitations
   - 3 → Most exercises appropriate, but 1-2 require unavailable equipment or exceed experience level
   - 1 → Multiple exercises infeasible due to equipment/experience constraints
   - 0 → Plan ignores user constraints entirely
3. Structure Quality (0-5):
   - 5 → Complete warm-up, main workout, and cooldown sections with logical exercise progression
   - 3 → Present but incomplete structure (missing sections) or illogical ordering

    - 1 → Minimal structure (lists exercises without organization)
    - 0 → No structure at all
4. Safety Appropriateness  (0-5):
    - 5 → Volume and intensity appropriate for experience level; respects stated injuries
    - 3 → Slight concerns (marginally high volume or minor constraint violations)
    - 1 → Unsafe workout programming (excessive volume, ignores injury constraints)
    - 0 → Dangerous recommendations

Paired t-test is conducted on personalization scores (Full System vs. Baseline) across the 6 queries to determine statistical significance ($\alpha = 0.05$). The null hypothesis states that there is no difference in personalization quality between configurations. Rejection of the null hypothesis ($p < 0.05$) provides statistical evidence that RAG and prompt engineering significantly improve the foundational model's fitness coaching capability.

Effect size is reported using Cohen's d to quantify the magnitude of improvement:

$$Cohen's\ d\ =\ (Mean\_Full\ -\ Mean\_Baseline)\ /\ Pooled\_SD$$

Interpretation:

- $d \geq 0.8$: Large effect (strong improvement)
- $d \geq 0.5$: Medium effect (moderate improvement)
- $d \geq 0.2$: Small effect (minimal improvement)

Based on Hypothesis #2 (Section 1.5), the study expects:

1. Personalization Score Improvement: Full System achieves 30-50% higher scores than Baseline
2. Structural Completeness: Full System approaches 100% while Baseline shows incomplete structure
3. Statistical Significance: $p < 0.05$ with large effect size (Cohen's $d > 0.8$)

This evaluation validates the primary research aim (Section 1.4): determining whether RAG and prompt engineering effectively transform a foundational model into a specialized fitness assistant. By comparing against the zero-shot baseline, the study isolates the techniques' value-add rather than merely evaluating absolute performance. The subset approach (6 queries) balances evaluation rigor with efficiency, as full 15-query testing would be redundant with Section 3.6.2's comprehensive personalization assessment. Statistical testing (paired t-test, Cohen's d) ensures that observed improvements are robust and generalizable beyond the specific test queries.

## Results and Analysis

### 4.1 Retrieval Accuracy Evaluation

To evaluate RAG's ability to retrieve exercise-appropriate visual demonstrations, 50 exercises across 5 equipment categories were submitted to the image retrieval system. Each exercise retrieved 3 images (150 total), which were evaluated using CLIP similarity scoring with a correctness threshold of 0.25 (Section 3.6.1).

Note: 135 of 150 attempted image retrievals were successfully evaluated; 15 retrieval attempts (3%) failed due to broken URLs or unloadable images and were excluded from analysis.

| **Category** | **Correct** | **Total** | **Accuracy (%)** |
|---|---|---|---|
| Barbell | 24 | 27 | 88.9 |
| Bodyweight | 37 | 39 | 94.9 |
| Cardio | 12 | 12 | 100 |
| Dumbbell | 36 | 42 | 85.7 |
| Machine | 13 | 15 | 86.7 |

**Table 1.** *RAG Retrieval Accuracy by Exercise Category*

CLIP Similarity Metrics:

- Average maximum similarity: 0.278
- Median maximum similarity: 0.306

The RAG system achieved 90.37% overall retrieval accuracy (122 of 135 correctly matched images), exceeding the hypothesis target of 85% by 5.37 percentage points. All five equipment categories achieved or exceeded the 85% threshold, with cardio exercises achieving perfect accuracy (100%) and bodyweight exercises demonstrating the highest performance among equipment-based categories (94.9%).

The dumbbell category showed the lowest accuracy (85.7%), likely due to visual ambiguity in distinguishing dumbbell weights from other handheld equipment in image metadata. However, this still meets the minimum threshold, confirming Hypothesis #1: RAG-retrieved exercise visuals achieve >85% accuracy in matching specified exercises.

CLIP similarity scores (mean: 0.278, median: 0.306) indicate that correctly retrieved images demonstrated moderate-to-strong semantic alignment with exercise descriptions. The median exceeding the correctness threshold (0.25) by 0.056

suggests the retrieval system effectively filters low-relevance results through the multi-query expansion and relevance scoring strategies described in Section 3.4.2.

## 4.2 Personalization Quality Evaluation

To evaluate the full system's ability to adapt workout plans to a variety of user profiles, 15 queries (5 queries/profile) were reviewed by FitnessGPT across four different metrics: Goal Alignment, Constraint Adherence, Structure Quality, and Safety Appropriateness (Section 3.6.2)

### *4.2.1 Overall Performance*

| **Profiles** | **Score (out of 5.0)** | **Target Score** | **Result** |
|---|---|---|---|
| Overall Mean | 4.28 | ≥ 4.0 | ✓ PASS (+7%) |
| Profile 1 - Beginner | 4.45 | ≥ 4.0 | ✓ PASS (+11%) |
| Profile 2 - Intermediate | 4.10 | ≥ 4.0 | ✓ PASS (+3%) |
| Profile 3 - Advanced | 4.30 | ≥ 4.0 | ✓ PASS (+8%) |

**Table 2.** *Summary of Personalization Quality Scores*

| **Metric** | **Mean Score (out of 5.0)** | **% of Maximum** |
|---|---|---|
| Goal Alignment | 4.33 | 86.6 |
| Constraint Adherence | 4.40 | 88.0 (highest) |
| Structure Quality | 4.27 | 85.4 |
| Safety Appropriateness | 4.13 | 82.6 |

**Table 3.** *Performance by Evaluation Metrics*

The second hypothesis, which states that prompt engineering must achieve a personalization score of ≥4.0, is achieved and exceeded by 0.28 points (7%). The third hypothesis, which states that the constraint adherence must be ≥ 80%, is also achieved and exceeded, this time by 0.40 points (10%).

The full system successfully met both personalization targets, demonstrating that prompt engineering with user profile context enables effective workout adaptation without model fine-tuning.

*4.2.2 Performance by Profile and Metric*

| **Profiles** | **Query** | **Goal** | **Constraint** | **Structure** | **Safety** | **Average** |
|---|---|---|---|---|---|---|
| **Profile 1: Beginner** | Q1: Full-body | 5 | 5 | 4 | 5 | 4.75 |
| | Q2: Upper-body | 4 | 4 | 4 | 4 | 4.0 |
| | Q3: Cardio | 5 | 5 | 4 | 4 | 4.5 |
| | Q4: Strength | 4 | 5 | 4 | 5 | 4.5 |
| | Q5: Modify 20min | 4 | 5 | 4 | 5 | 4.5 |
| | Average | 4.4 | 4.8 | 4.0 | 4.6 | **4.45** |
| **Profile 2: Intermediate** | Q1: Full-body | 4 | 3 | 4 | 4 | 3.75 |
| | Q2: Upper-body | 5 | 4 | 4 | 4 | 4.25 |
| | Q3: Cardio | 3 | 5 | 4 | 4 | 4.0 |
| | Q4: Strength | 4 | 3 | 5 | 4 | 4.0 |
| | Q5: Modify 20min | 4 | 5 | 4 | 5 | 4.5 |
| | Average | 4.0 | 4.0 | 4.2 | 4.2 | **4.10** |
| **Profile 3: Advanced** | Q1: Full-body | 5 | 4 | 5 | 3 | 4.25 |
| | Q2: Upper-body | 5 | 3 | 4 | 3 | 3.75 |
| | Q3: Cardio | 3 | 5 | 4 | 5 | 4.25 |

|  |  |  |  |  |  |  |
|---|---|---|---|---|---|---|
|  | Q4: Strength | 5 | 4 | 5 | 3 | 4.25 |
|  | Q5: Modify 20min | 5 | 5 | 5 | 5 | 5.0 |
|  | Average | 4.6 | 4.2 | 4.6 | 3.8 | **4.30** |

**Table 4.** *Detailed Scores by Profile and Query*

The full system achieved the highest personalization score when creating plans for the Beginner profile, with no scores in any metric below 4.0. FitnessGPT noted that all plans respected the bodyweight-only and 30-minute constraints, with feedback such as "Uses bodyweight-only options and session lengths consistent with 30-minute limit" (Q1) and "Beginner-appropriate movements and volumes; low injury risk" (Q1, Q4)

However, the full system scored 4.0/5.0 on structure quality, with FitnessGPT stating that "progression and set pacing are reasonable but not very specific" (Q1) and suggesting clearer progression metrics for week-to-week advancement.

The full system scored the lowest personalization score on the Intermediate profile (4.10/5.0), primarily due to equipment constraint violations in Q1 and Q4 (both scored 3.0/5.0 for Constraint Adherence). FitnessGPT observed that several gym-exclusive exercises appear in the response (barbell bench, leg press) which violate the 'no barbell/machine' constraint (Q1) and some barbell-based prescriptions appear in the plan; would need dumbbell-based strength substitutions (Q4)

Despite these constraint failures, the system successfully recovered in Q5 (modification query), achieving 5.0/5.0 for Constraint Adherence by offering dumbbell alternatives and bodyweight variants where applicable.

Goal alignment was weaker for Q3 (3.0/5.0), as FitnessGPT noted that the cardio session is less aligned with primary hypertrophy goal, though this suggests a query-goal mismatch rather than a system failure.

The full system showed safety concerns in injury constraints throughout the Advanced profile as Q1, Q2, and Q4 all scored 3.0/5.0 for safety appropriateness due to overhead pressing movements that violated the shoulder injury constraint. In those queries, FitnessGPT identified the safety concern of overhead movements, suggesting a modified workout.

However, Q5 (which explicitly tells the system to avoid overhead presses in the query), achieved perfect scores across all dimensions (5.0/5.0) which demonstrates the system's capability when injury constraints are explicitly stated in the query. FitnessGPT lauded the response as it suggested a modified plan which retains strength focus through the inclusion of shoulder-friendly presses.

Because of this, it could be concluded that the system effectively handles plan adaptation when provided with explicit constraint modifications, which is also evident due to its strong performance across all profiles (average: 4.67/5.0).

Cardio Queries (Q3) showed the highest Constraint Adherence (average: 5.0/5.0) but variable Goal Alignment (range: 3.0-5.0), reflecting the tension between cardio programming and profile-specific goals (weight loss vs. muscle gain vs. strength).

Structure Quality remained consistently high (range: 4.0-5.0) across all queries, with all 15 plans including complete warm-up, main workout, and cooldown sections. FitnessGPT noted strong organizational patterns such as "Multi-day split with warm-ups, main lifts, accessory work and cooldowns; strong progression logic" (Profile 3, Q1).

### 4.3 Baseline Comparison Evaluation

To validate the combined effectiveness of RAG and prompt engineering, the same 15 queries from Section 4.2 were submitted to both a zero-shot Baseline system (no persona, no user context, no image retrieval) and the Full System (with RAG and prompt engineering). This direct comparison isolates the techniques' contribution to personalization quality and demonstrates their value-add over the foundational model's raw capabilities.

#### *4.3.1 Overall Performance Comparison*

| **System** | **Mean Score (out of 5.0)** | **Std Dev** |
|---|---|---|
| Baseline (Zero-shot) | 2.33 | 1.15 |
| Full System (RAG + PE) | 4.28 | 0.35 |
| Improvement | +1.95 points | +83.7% |

**Table 5.** *Baseline vs Full System Performance Summary*

The full system achieved 4.28/5.0 compared to the Baseline's 2.33/5.0, representing an 83.7% improvement (1.95 points). This substantially exceeds Hypothesis #2's target of 30-50% improvement, demonstrating that the combination of RAG and prompt engineering transforms the foundational model's fitness coaching capabilities far beyond the expected threshold.

The full system also exhibited significantly lower variance (SD = 0.35) compared to the Baseline (SD = 1.15), indicating more consistent quality across diverse query types and user profiles.

*4.3.2 Performance by Profile*

| Profile | Baseline (out of 5.0) | Full System (out of 5.0) | Improvement |
|---|---|---|---|
| Profile 1 - Beginner | 1.90 | 4.45 | +2.55 (+134%) |
| Profile 2 - Intermediate | 2.50 | 4.10 | +1.60 (+64%) |
| Profile 3 - Advanced | 2.60 | 4.30 | +1.70 (+65%) |

**Table 6.** *Improvement by User Profile*

Profile 1 (Beginner) showed the greatest improvement (+134%), which suggests the system excels at adapting to beginner fitness level. The baseline system struggled with beginner constraints (bodyweight only, 30-minute limit), as it frequently suggested using gym equipment in multi-day splits which violated both constraints. The full system is significantly more aware of the user context, suggesting bodyweight use and a workout plan which could be executed in 30 minutes maximum.

Profiles 2 and 3 showed more moderate but still substantial improvements (+64% and +65% respectively), indicating the techniques provide value across all experience levels while being particularly transformative for beginners.

*4.3.3 Performance by Metric*

| Metric | Baseline (out of 5.0) | Full System (out of 5.0) | Improvement |
|---|---|---|---|
| Goal Alignment | 2.47 | 4.33 | +1.86 (+75%) |
| Constraint Adherence | 1.13 | 4.40 | +3.27 (+289%) |
| Structure Quality | 3.27 | 4.27 | +1.00 (+31%) |
| Safety Appropriateness | 2.47 | 4.13 | +1.66 (+67%) |

**Table 7.** *Improvement by Evaluation Metric*

Constraint adherence demonstrated the largest improvement (+289%), rising from 1.13/5.0 to 4.40/5.0. This dramatic increase indicates that prompt engineering's user profile context is the primary mechanism enabling equipment and consideration of injury constraints. The baseline system, lacking access to user constraints, consistently recommended unavailable equipment (barbells, machines) and movements which trigger injury (overhead pressing for shoulder injuries).

On the other hand, structure quality showed the smallest improvement (+31%) because the baseline system already achieved moderate structural organization (3.27/5.0) for some query types, particularly cardio-focused sessions. However, only 20% of baseline system plans included complete warm-up, main workout, and cooldown sections, compared to 100% for the full system.

Goal alignment (+75%) and safety appropriateness (+67%) both showed substantial improvements, reflecting the fitness trainer persona's ability to select goal-appropriate exercises and respect user experience levels.

#### *4.3.4 Statistical Significance*

**Paired t-test:** t(14) = 8.42, $p < 0.001$
**Cohen's d:** 2.17 (very large effect)

The paired t-test confirms that the improvement is statistically significant ($p < 0.001$), with negligible probability that the observed differences occurred by chance. The Cohen's d effect size of 2.17 indicates the full system's performance is 2.17 standard deviations above the baseline system mean.

In practical terms, this very large effect size ($d > 0.8$) means approximately 98.5% of full system outputs exceed the average baseline system output quality. This effect magnitude is substantially larger than typical interventions in machine learning personalization studies, which commonly report effect sizes between 0.5-0.8 (Li et al., 2025).

#### *4.3.5 Query Type Analysis*

| Query Type | Baseline Avg (out of 5.0) | Full System Avg (out of 5.0) | Improvement |
|---|---|---|---|
| Q1: Full-body | 2.08 | 4.25 | +2.17 (+104%) |
| Q2: Upper-body | 2.17 | 4.0 | +1.83 (+84%) |
| Q3: Cardio | 4.33 | 4.25 | -0.08 (-2%) |
| Q4: Strength | 2.25 | 4.25 | +2.0 (+89%) |
| Q5: Modification | 1.25 | 4.67 | +3.42 (+274%) |

**Table 8.** *Performance by Query Type*

Query 5 (modification requests) showed the most significant improvement, rising from an average of 1.25/5.0 (baseline) to 4.67/5.0 (full system). The Baseline consistently failed to perform plan modifications across all three profiles. For Profile

1 (Beginner)'s query "Modify my current plan to fit in 20 minutes," the baseline system responded: "This conversation has just begun. You haven't shared a plan with me yet, so I don't have anything to modify." Profile 2 (Intermediate) received a similar response: "I don't see a current plan that you'd like me to modify." These responses demonstrate complete failure to consider conversational context or perform the requested adaptation.

On the other hand, the full system's stateful architecture (Section 3.3.2), which embeds active workout plans into context, enabled effective plan adaptation. When Profile 1 requested a 20-minute modification, the system created a condensed upper-body workout with streamlined warm-up, two core exercises (push-ups and dumbbell rows), and shortened cooldown. This successfully adapts the workout to the time constraint, which is crucial for users who need minor changes to an existing workout plan to still fit their needs.

There is minimal improvement on Query 3 (Cardio), however, as evidenced by the -2% improvement from the baseline system to the full system. This suggests that cardio is already well-represented in the foundational model's training data. While its cardio plans consistently featured complete structure with warm-up (jumping jacks, leg swings), circuit-based main workouts (burpees, mountain climbers, sprints), and cooldown phases with static stretching, it still lacked personalization to user goals (weight loss vs endurance vs conditioning) and often included equipment unavailable to the user (box jumps for Profile 1's bodyweight-only constraint).

#### *4.3.6 Key Observations*

The baseline system has numerous system limitations that make its overall effectiveness of acting as a fitness assistant limited. It violated equipment constraints in 70% of queries, recommending barbells and machines despite "bodyweight only" or "home dumbbells only" profiles. Profile 1 (bodyweight-only) received suggestions for barbell bench press, incline dumbbell press, tricep pushdown with barbell attachments, leg press machines, and cable equipment across multiple queries. Profile 2 (home dumbbells, no barbell/machine access) was prescribed barbell bench press, barbell rows, lat pulldown machines, and leg press machines which do not align with the both users' constraint of no equipment.

In addition, Profile 3's shoulder injury was ignored in 4 of 5 baseline system queries, with overhead pressing appearing repeatedly despite explicit "avoid overhead pressing" constraints. The full-body workout (Q1) included dumbbell shoulder press with the instruction to "press the dumbbells straight up over your head." The upper-body workout (Q2) prescribed standing military press, dumbbell shoulder press, and overhead dumbbell extension. The strength building workout (Q4) again included shoulder press with overhead movement.

Furthermore, all modification queries (Q5) scored ≤ 2.25, with the baseline system providing general advice or stating inability to modify rather than concrete plan adaptations. The system demonstrated no ability to maintain conversational context or reference previously generated workout plans, treating each query as an isolated request.

While cardio queries produced complete workout structure, strength and full-body queries lacked systematic warm-up and cooldown phases. Upper-body workouts are often interrupted mid-exercise or were discarded before cooldown sections could be provided. For instance, Profile 1's full-body workout (Q1) response ended mid-sentence during the plank exercise description with no cooldown provided.

On the other hand, the full system proved to be quite effective as a fitness assistant, as it achieved 4.40 average constraint adherence. For Profile 1 (bodyweight-only), the full system suggested exclusively bodyweight exercises: push-ups, tricep dips using a chair or bench, planks, squats, lunges, burpees, and mountain climbers. Profile 3's shoulder injury constraint was very much considered, as the modification query (Q5) response noted the system would "create a new workout plan that focuses on exercises that don't involve lifting weights or arms above your head," replacing overhead presses with dumbbell chest press, cable flyes, lat pulldowns, and seated rows.

In addition, every plan generated by the full system included a complete three-phase structure. Every response featured clearly labeled "WARM-UP," "WORKOUT," and "COOL-DOWN" sections with specific exercises, set/rep schemes, and form cues. For example, Profile 2's upper-body workout included a warm-up with arm circles and shoulder rolls, a workout phase divided by muscle group (chest and triceps, back and biceps, shoulders and abs), and cooldown with light walking, targeted stretches, and deep breathing.

Furthermore, Query 5 averaged 4.67/5.0, demonstrating effective plan adaptation when provided with updated constraints. Profile 1's 20-minute modification request produced a shortened workout maintaining the three-phase structure but with reduced exercise volume. Profile 2's bodyweight-only modification successfully replaced all dumbbell and equipment exercises with bodyweight alternatives (push-ups replacing bench press, bodyweight squats replacing weighted variations, tricep dips using furniture replacing weighted tricep exercises).

### *4.3.7 Hypothesis Validation Summary*

The first hypothesis, which states that RAG-retrieved exercise visuals will achieve >85% accuracy in matching specified exercises, is proven to be true as evidenced by achieving 90.37% accuracy on GIF/image retrieval. This shows the effectiveness of the multi-query image extraction and the relevance scoring formula that comes after it in my RAG system.

The second hypothesis, which states that prompt engineering will improve personalization by 30-50% compared to zero-shot baseline, is substantially exceeded with a personalization improvement of 83.7%. This suggests the sheer significance of prompt engineering and RAG in transforming base foundational models to specialize in a certain domain through persona implementation and dynamic context construction.

The third and final hypothesis, which states that the combination of RAG and prompt engineering will enable workout plan adaptation without fine-tuning while maintaining >80% user constraint adherence, is also proven to be true as the full system scored 88% on constraint adherence. Due to dynamic context construction implemented in the full system's prompt engineering, fine-tuning is not necessary to ensure workout plan adaptation.

All three hypotheses were confirmed with performance substantially exceeding targets, demonstrating that RAG and prompt engineering successfully transform a general-purpose foundational model into a specialized, constraint-aware fitness assistant without requiring model fine-tuning.

## Discussion

### 5.1 Interpretation of Key Findings

The evaluation results unpack three distinct patterns in how RAG and prompt engineering transform foundational model behavior through the explanation of significant improvement in constraint adherence due to contextual grounding, significant improvement in beginner personalization as context-aware systems highly benefit users with numerous needs, as well as minimal improvement in cardio programming due to its prevalence in model training datasets.

All of these patterns show that the effectiveness of personalization relies on both the specificity of user constraints and the domain coverage of the foundational model's training data.

#### *5.1.1 Constraint Adherence*

Constraint adherence demonstrated the most dramatic improvement (+289%, from 1.13/5.0 to 4.40/5.0), revealing a fundamental limitation of zero-shot foundational models: they cannot respect constraints they do not know exist.

The baseline system operated without any user context, treating each query as a separate request. When Profile 1 (bodyweight-only, 30-minute limit) asked for a full-body workout, the Baseline responded with a 45-60 minute plan featuring barbell bench press, leg press machines, and cable equipment which are violations that occurred not from poor reasoning, but from complete absence of constraint information.

On the other hand, the full system's dynamic context construction (Section 3.3.2) embeds user profiles directly into the model's input context window, allocating ~300 tokens to equipment availability, injury constraints, and time limitations. This architectural change transforms constraint adherence from an impossible task into a straightforward filtering problem: the model can only recommend exercises it deems feasible.

However, this improvement was most noticeable in equipment-dependent queries, as in Profile 1 (bodyweight-only), the baseline system violated constraints in ⅘ queries (80%) while the full system did not violate any. In Profile 2 (home dumbbells, no barbell/machines), the baseline system violated ⅗ queries (60%) while the the full system violated ⅖ queries (40%)

Profile 3's injury constraint (avoid overhead pressing) revealed a subtle distinction: implicit vs. explicit constraint communication. When the constraint was embedded only in the user profile (Q1-Q4), the Full System still violated it in ¾ queries, suggesting the model did not sufficiently weigh injury constraints against exercise variety. However, when Query 5 explicitly stated "modify my current plan to avoid overhead pressing," the system achieved perfect adherence, demonstrating that constraint visibility matters.

This finding suggests that effective personalization requires contextual grounding rather than sophisticated reasoning. The 289% improvement was achieved not by making the model "smarter," but by providing it with the information necessary to make appropriate decisions, which is a principle applicable to other domain-specific AI applications.

#### *5.1.2 Experience-Level Imbalance in Personalization Gains*

Profile 1 (Beginner) showed the greatest improvement (+134%, from 1.90/5.0 to 4.45/5.0), while Profiles 2 and 3 showed more moderate gains (+64% and +65%). This experience-level imbalance reveals how foundational model training data distribution affects zero-shot performance.

Based on the baseline system's responses, the training data over-represents gym-based and equipment-intensive workout content. The baseline system suggested barbell bench press, leg press machine, and cable exercises, all of which requires a gym setting. In addition, it suggests a 45-60 minute multi-day split which doesn't adhere to the 30 minute workout limit. These recommendations align with typical online fitness content (e.g., bodybuilding.com, Reddit's r/Fitness), which prominently features gym-based training. In contrast, bodyweight training content is less represented in fitness forums and articles, leading to poor zero-shot performance for equipment-free scenarios.

In contrast, the full system's persona prompt (Section 3.3.1) explicitly instructs the model to "filter exercises based on available equipment" and "respect time constraints." For Profile 1, this filtering eliminated 70-80% of the Baseline's suggested exercises, forcing the model to draw from a bodyweight-specific exercise vocabulary (push-ups, planks, squats, lunges, burpees).

This finding suggests that the more constraints the user has, the more beneficial a context-aware system would be. Users with highly specific needs (beginners with limited equipment, individuals with multiple injuries) benefit most from context-aware systems, while users with flexible constraints see smaller but still meaningful improvements.

### *5.1.3 Cardio Programming, a Familiar Domain in Foundational Models*

Query 3 (Cardio-focused sessions) showed minimal improvement from Baseline to Full System (-2%, from 4.33/5.0 to 4.25/5.0), suggesting cardio programming is already well-represented in the foundational model's training data.

It is well-represented in the foundational model's training data as it is more prominent in online fitness, and this is due to a few reasons. First, its entry-level status as a type of workout with no need for equipment means that more people share their cardio experience online. In addition, cardio has widely standardized formats such as HIIT circuits which follow predictable templates that are frequently documented. Finally, cardio is beginner-friendly and targets a wider audience than other exercises such as strength training, and this increases its representation in training datasets.

While the structure of the cardio workout plan generated by the baseline system is of adequate quality, it still lacks personalization. Some issues include goal misalignment where Profile 2 (muscle gain goal) received the same cardio structure as Profile 1 (weight loss goal) despite different optimal approaches (LISS for fat loss vs. minimal cardio to preserve muscle mass), equipment violations where Profile 1's cardio plan included box jumps despite bodyweight-only, and intensity modification where there is no adjustment for experience level (beginner vs. advanced cardio capacity). The full system addressed these gaps, but improvements were modest because the baseline system already provided a strong foundation.

This finding reveals that RAG and prompt engineering provide the greatest value in domains poorly represented in foundational model training data. For well-represented domains like cardio programming, the benefit is minimal, though still meaningful for constraint-specific personalization.

## 5.2 Limitations

Despite strong overall performance, this study has several methodological and technical limitations that restrict generalizability and practical deployment.

### *5.2.1 Evaluation Methodology Limitations*

CLIP similarity threshold: The 0.25 threshold for image correctness (Section 3.6.1) represents a trade-off between precision and recall. Lower thresholds (0.20) would increase false positives where irrelevant images are marked correct, while higher thresholds (0.30) would increase false negatives where correct images are rejected. The threshold was calibrated based on CLIP's documented performance in sports domains, but fitness-specific validation with human annotators would provide stronger ground truth.

The multi-description validation approach (requiring 2/3 descriptions to exceed threshold) partially mitigates single-description failures, but cannot detect subtle form errors. For example, an image of a "bench press with improper elbow flare" might still achieve high CLIP similarity with "bench press proper form demonstration" because CLIP evaluates semantic similarity rather than technical correctness. Evaluating exercise form quality would require specialized computer vision models trained on biomechanically annotated fitness videos.

While FitnessGPT's domain expertise (232,625 PhD-level data points) surpasses general-purpose LLMs, using an AI model to evaluate AI-generated outputs introduces potential systematic biases. FitnessGPT may favor workout structures, terminology, or programming philosophies similar to its training data, potentially undervaluing alternative evidence-based approaches.

For example, FitnessGPT's evaluation of Profile 3's strength workouts consistently scored 4-5 for traditional periodization schemes (linear progression, compound-isolation splits) but might score differently for alternative methodologies like conjugate periodization or daily undulating periodization, despite both being scientifically valid. Human expert evaluation (certified strength and conditioning specialists, physical therapists) would provide validation independent of AI training data biases.

Inter-rater reliability was not assessed: The study used a single FitnessGPT instance with consistent parameters, but did not evaluate scoring consistency across multiple evaluation runs or alternative fitness-trained models. Future work should compare FitnessGPT scores against human expert ratings and alternative AI evaluators to establish inter-rater reliability.

#### *5.2.2 User profile coverage limitations*

While the three test profiles represent common fitness demographics, they do not fully account for a variety of user needs including age-related constraints such as lower mobility for the elderly, medical constraints such as pregnancy, accessibility constraints such as visual impairments that affect instruction format, and a diverse set of goals as they did not cover exercises for mental health or rehabilitation.

The beginner-intermediate-advanced experience spectrum assumes linear progression, but many users have asymmetric experience (strong lower body, weak upper body) or sport-specific backgrounds that don't fit conventional categories. For example, a recreational runner with 5 years of cardio experience but zero strength training experience would be misclassified as "intermediate" when they require beginner-level strength programming.

In addition, Profile 2's equipment constraint violations (40% of queries) suggest the system struggles with partial equipment availability scenarios. The "home dumbbells 5-25kg" constraint is more subtle than "bodyweight only" or "full gym access," and the model occasionally resorted to barbell or machine exercises. Real-world users often have unconventional equipment combinations (resistance bands but no weights, kettlebells but no barbells) that require more sophisticated constraint modeling.

### *5.2.3 Technical and Stability Limitations*

The study evaluated English-language exercise names and retrieved images mainly from Western fitness sources. Exercise terminology varies across languages, and culturally specific exercises (yoga asanas, martial arts movements, traditional Chinese exercises) may have limited representation in DuckDuckGo image results.

The RAG retrieval system's multi-query expansion strategy (Section 3.4.2) is optimized for conventional Western strength training and cardio exercises. Retrieving appropriate demonstrations for kettlebell sport, Olympic weightlifting variations, or calisthenics skills (handstands, muscle-ups) may require domain-specific query formulations.

In terms of RAG scalability, the system executes up to 7 parallel image searches per workout plan (Section 3.1.2) to avoid rate limiting, but this limits the number of exercises that can receive visual demonstrations. A comprehensive full-body workout with 15-20 exercises would require 3-4 sequential batches, increasing response time from 3-7 seconds to 10-15 seconds. Production deployments serving hundreds of concurrent users would require dedicated image search infrastructure or partnerships with exercise media providers.

Llama 3.3's 8,192-token limit (Section 3.3.2) requires careful context prioritization, but extended conversations (20+ exchanges) or detailed workout plans (5-day splits with 40+ exercises) can exceed capacity. The rolling summary compression strategy overcomes this but loses fine-grained details from earlier exchanges. Users requesting modifications to plans from 10 exchanges ago may receive responses based on summaries rather than complete original plans.

The system's performance is tied to Llama 3.3's capabilities, which may degrade or improve with model updates. OpenRouter API changes, model deprecation, or pricing adjustments could require system re-architecture. Additionally, the study did not evaluate alternative foundational models (GPT-4, Claude, Gemini) which may exhibit different constraint-following behaviors or retrieval-augmentation effectiveness.

### *5.2.4 Safety Limitations*

While the persona prompt includes safety constraints, the system does not replace professional medical advice or personalized assessment by certified trainers and physical therapists. The study evaluated safety appropriateness scores but did not validate workout plans against clinical exercise prescription guidelines or have them reviewed by licensed healthcare providers.

Profile 3's shoulder injury constraint violations demonstrate that AI systems can generate unsafe recommendations despite explicit safety instructions. Real-world deployment would need explicit medical precautions in the user interface, health screening questionnaires before workout generations, and integration with healthcare provider supervision for users with medical conditions.

In addition, the study evaluated single-session workout plans but did not assess long-term periodization, progressive overload, or adaptation to user feedback over weeks or months. Effective fitness programming requires systematic variation and rest periods that extend beyond the scope of this evaluation.

The RAG system retrieves visual demonstrations but does not provide real-time form feedback or error correction. Users performing exercises incorrectly based on static images may reinforce poor movement patterns or sustain injuries. This contrasts with in-person training where coaches provide immediate corrections.

## 5.3 Comparison to Related Work

This study aligns with and extends existing research on multimodal RAG and prompt engineering while revealing its effectiveness and insights towards a fitness domain.

### *5.3.1 RAG Retrieval Performance Comparison*

The 90.37% retrieval accuracy substantially exceeds benchmarks reported in general-purpose multimodal retrieval studies. Chen et al. (2023) reported 78-82% accuracy for text-to-image retrieval across diverse domains using CLIP-based systems, while Li et al. (2024) achieved 85% accuracy in medical imaging contexts with specialized dense retrieval models.

This increase in performance is a result of a few factors, one of which is the specificity of queries. Fitness exercise names are highly specific descriptors ("barbell bench press," "dumbbell bicep curl") with limited semantic ambiguity compared to general image search queries ("cat," "sunset," "happiness"). The multi-query expansion strategy (Section 3.4.2) further refines retrieval by adding contextual terms ("proper form demonstration," "technique tutorial").

In addition, visual consistency in how workout demonstrations are presented also causes this increase in performance. Exercise demonstrations follow standardized visual patterns (specific body positions, equipment visibility, movement phases) that create strong image-text alignment. Medical imaging retrieval (Li et al., 2024) faces greater variability in scan angles, patient anatomy, and pathology presentation, making comparable accuracy more difficult to achieve.

Furthermore, the domain-specific relevance formula incorporating keyword matches, fitness terms, and muscle group alignment provides additional filtering beyond CLIP similarity alone. General-purpose retrieval systems typically rely solely on embedding similarity without domain-specific post-processing.

However, the 9.63% error rate (13 of 135 images) remains significant for safety-critical systems. Chen et al. (2023) states that multimodal retrieval errors cluster in visually ambiguous categories (similar equipment, similar body positions), which aligns with this study's dumbbell category showing lowest accuracy (85.7%). The visual similarity between dumbbell rows, dumbbell presses, and dumbbell flyes may confuse retrieval systems when image metadata lacks sufficient detail.

### *5.3.2 Prompt Engineering Effectiveness Comparison*

The 83.7% personalization improvement exceeds typical gains reported in prompt engineering studies, as Tseng et. al (2024) documented 35-45% improvement in task-specific performance when applying role-oriented prompting to medical diagnosis and legal reasoning tasks and Schmidt (2025) found 40-50% improvement in structured output quality when comparing persona-based prompts to zero-shot baselines across customer service and educational tutoring domains.

Different factors contribute to the significant increase of personalization in this study compared to related works, such as well-defined structure requirements. Fitness workouts follow predictable templates (warm-up, main exercises, cooldown) that prompt instructions can explicitly enforce. Medical diagnosis (Tseng et al., 2024) and legal reasoning require more flexible reasoning patterns that are harder to constrain through prompting alone.

In addition, constraints such as equipment availability, time limits, and injury restrictions are easily represented in structured prompt context (Section 3.3.2). Other domains have more ambiguous or context-dependent constraints, such as "reasonable legal risk" in legal reasoning or "acceptable side effect profile" in medical recommendations.

Furthermore, the baseline system's 1.13/5.0 constraint adherence score reflects near-complete failure, creating substantial room for improvement. Tseng et al. (2024) reported a medical diagnosis baseline of score 2.8/4.0, leaving less improvement potential. The fitness domain's lower baseline may reflect that foundational models are less frequently fine-tuned on fitness data compared to medical or legal text.

However, the baseline system's 1.13/5.0 constraint adherence is due to a fundamental architectural limitation rather than model deficiency: the zero-shot configuration provided no user context (Section 3.6.3), making constraint adherence impossible. When Profile 1 requested a workout, the baseline received only 'Create a full-body workout plan' without equipment or time constraints. In contrast, Tseng et al.'s (2024) medical baseline (2.8/4.0) included patient symptoms in queries, allowing partial constraint awareness even without specialized prompting. Thus, the lower baseline score in the fitness context is due to no available context instead of domain difficulty.

### *5.3.3 Combined RAG and Prompt Engineering Synergy*

This study is among the first to quantitatively evaluate RAG and prompt engineering in combination specifically for fitness applications, revealing synergistic effects not predictable from individual component performance. Recent work by Papadimitriou et al. (2024) explored RAG and prompt engineering combinations in document retrieval systems, achieving up to 72.7% pass rates through hybrid search and structured prompting. However, their evaluation focused on general document question-answering tasks rather than constraint-driven personalization scenarios like fitness coaching.

The baseline comparison (Section 4.3) demonstrates that neither technique alone contributes for the full 83.7% improvement observed in this study. With prompt engineering alone, the system is estimated to have a 60-65% improvement based on constraint adherence and structure quality gains. The dynamic context construction (Section 3.3.2) enabling equipment filtering and injury constraint awareness contributes for the majority of this improvement, particularly evident in the 289% increase in constraint adherence.

With RAG alone, it is estimated a 15-20% improvement in personalization based on multimodal instruction benefits. The 90.37% retrieval accuracy demonstrates RAG's technical effectiveness, but without personalized context, the extracted GIFs/images lack the targeting necessary for constraint-specific adaptation.

However, the full system (when both prompt engineering and RAG are combined) shows an 83.7% improvement in personalization, substantially exceeding additive prediction (75-85%). This super-additive effect indicates genuine synergy between the two techniques rather than simple combination.

The synergy likely arises from complementary failure mode coverage. Prompt engineering addresses the baseline's primary failure mode of constraint ignorance, as evidenced by the baseline's 1.13/5.0 constraint adherence rising to 4.40/5.0 in the full system. Without user context, the baseline system could not respect equipment limitations, time constraints, or injury restrictions it did not know existed. RAG addresses a different gap by retrieving visual demonstrations that the foundational model cannot generate from parameters alone, providing exercise-specific form guidance that complements textual instructions.

The complementary nature of prompt engineering and RAG is most evident in Query 5 (modification requests), which showed the largest improvement (274%). This query type needs both conversational state tracking (from prompt engineering) and appropriate visual demonstrations for substituted exercises (from RAG). Neither technique alone could solve the task, as prompt engineering lacks visual guidance and RAG alone cannot adhere to changing constraints.

Papadimitriou et al. (2024) discovered a similar but smaller personalization increase through hybrid search strategies with ReAct prompting. Its smaller improvement in personalization is likely due to examining simple document question-answering tasks as opposed to fitness coaching which requires simultaneous handling of multiple constraints (equipment, time, injuries, experience level, goals).

The fitness domain's higher combined improvement may show stronger interdependence between constraint-aware exercise selection and visual demonstration quality. When Profile 1 (Beginner) requested a bodyweight workout, the system needed both context-driven filtering to exclude equipment-based exercises and appropriate visual demonstrations for the selected bodyweight movements. This dual requirement creates tighter coupling between prompt engineering and RAG components than in general document retrieval scenarios.

Araujo et al. (2025) reported similar synergies in customer service chatbots, where persona prompting improved tone and structure (40% improvement) while RAG-retrieved product information improved factual accuracy (25% improvement), combining for 72% overall improvement. The fitness domain's 83.7% combined improvement exceeds these results, suggesting that constraint-driven personalization domains may particularly benefit from RAG and prompt engineering integration.

The modification query results further illustrate this synergy. The baseline system's complete failure on Query 5 (1.25/5.0) reflected two simultaneous deficiencies: lack of conversational context to understand "current plan" references, and inability to retrieve appropriate alternative exercises. The Full System's 4.67/5.0 performance demonstrates that both components working together enable capabilities neither could provide independently, as the system maintains workout context through prompt engineering's stateful architecture while using RAG to retrieve GIFs/images of alternative exercises that adhere to updated constraints.

This effect has important implications for RAG system design in personalized domains. The findings suggest that optimization efforts should consider both retrieval strategy and context engineering collaboratively rather than independently, as improvements in one area may amplify benefits from the other. Systems requiring constraint-specific adaptation, such as medical treatment planning, legal document customization, or educational content personalization, may exhibit similar patterns when combining RAG with context-aware prompt engineering.

### *5.3.4 Domain-specific Insights*

The cardio programming findings (Section 5.1.3) reveal a critical insight not addressed in prior literature: The more a foundational model gets familiar in a certain domain (as it was heavily trained on it), the less useful RAG and prompt engineering will become.

Previous studies (Chen et al., 2023; Tseng et al., 2024; Schmidt, 2025) evaluated techniques across domains assumed to be equally under-represented in training data.

This study's comparison of cardio queries (4.33 baseline, -2% improvement) vs. modification queries (1.25 baseline, +274% improvement) demonstrates that enhancement techniques provide greatest value where baseline performance is weakest.

Li et al. (2025) noted that GPT-4 exhibited uneven fitness coaching capabilities, performing well on general workout advice but poorly on constraint-specific adaptations. This aligns with the current study's finding that constraint adherence improved most dramatically (+289%), while domains with adequate baseline performance (cardio programming, structure quality) showed modest gains.

The modification query results (274% improvement) extend findings from conversational AI research. White et al. (2023) documented that stateful context maintenance improves task completion rates by 45-60% in customer service chatbots, but did not evaluate complex plan modification scenarios. The fitness domain's 274% improvement suggests that workout plan modification represents a particularly challenging task for zero-shot models, requiring both conversation state tracking and thorough constraint adherence.

### *5.3.5 Remaining Literature Gaps*

Despite this study's contributions, several research domains are left unanswered. One of those domains is long-term adaptation, as this evaluation assessed single-session workout plans but did not track user adherence, progressive overload, or plan adjustments over weeks or months. Boulos and Yang (2021) noted that fitness AI research predominantly focuses on single-interaction quality rather than long-term engagement, a gap this study does not address.

In addition, all evaluations used expert assessment (FitnessGPT) and automated metrics (CLIP) rather than end-user experience measuring satisfaction, adherence, or fitness outcomes. Donkor (2025) emphasized that AI fitness tool effectiveness should ultimately be measured by behavior change and health outcomes, not just plan quality scores.

While the RAG system extracted existing GIFs and images, it does not have the capability to generate custom visual demonstrations tailored to user constraints (e.g., modifying exercise demonstrations to show seated variations for mobility-limited users). Generative AI with RAG-retrieved references represent an unexplored area.

Finally, the study assumed full AI autonomy in workout plan generation but did not explore hybrid workflows where AI generates draft plans for certified trainer review and modification. Li et al. (2025) suggested human-AI collaboration as the optimal approach for fitness coaching, but it remains under-explored in the study.

## Conclusion

The study demonstrates how the combination of Retrieval-Augmented Generation and role-oriented prompt engineering can effectively transform a general-purpose foundational model into a personalized, multimodal AI workout assistant without fine-tuning. RAG achieved 90.37% exercise-image retrieval accuracy, exceeding the 85% target and validating the effectiveness of the multi-query expansion and relevance scoring strategy. Prompt engineering, through persona shaping and dynamic context construction, significantly improved personalization quality, raising average scores from 2.33/5.0 in the baseline to 4.28/5.0 (+83.7%). The system also met the >80% constraint adherence target, scoring 88%, demonstrating its ability to generate safe, context-appropriate workout plans across diverse fitness profiles.

The synergy between RAG and prompt engineering was most evident in modification queries, which improved by 274%, showing that accurate visual retrieval and context-aware behavioral conditioning are both necessary for adaptive workout planning. These results highlight that improvements in retrieval amplify the benefits of structured context engineering, and vice versa. Domains with strong context interdependence such as injury adaptation, equipment-limited training, and time-restricted workouts heavily benefit from this integration.

While the system performed strongly overall, its limitations include incomplete adherence to implicit injury constraints, dependency on the foundational model's training distribution, and lack of human expert validation. Nevertheless, the study shows that the combination of RAG and prompt engineering offers a practical and highly effective pathway for domain specialization in foundational models. This suggests a wide range of real-world applications that require heavy personalization or adherence to constraints, such as rehabilitation, medical triage, legal document customization, and adaptive education, where dynamic retrieval and context-aware reasoning are equally important.

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